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CONSEQUENTIAL LCA

Consequential life cycle assessment: a review

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Abstract
Purpose Over the past two decades, consequential life cycle assessment (CLCA) has emerged as a modeling approach for capturing environmental impacts of product systems beyond physical relationships accounted for in attributional LCA (ALCA). Put simply, CLCA represents the convergence of LCA and economic modeling approaches.
Method In this study, a systematic literature review of CLCA is performed.
Results While initial efforts to integrate the two modeling methods relied on simple partial equilibrium (PE) modeling and a heuristic approach to determining affected technologies, more recent techniques incorporate sophisticated economic models for this purpose. In the last 3 years, Multi-Market, Multi-Regional PE Models and Computable General Equilibrium models have been used. Moreover, the incorporation of other economic notions into CLCA, such as rebound effects and experience curves, has been the focus of later research. Since economic modeling can play a prominent role in national policy-making and strategic/corporate environmental planning, developing the capacity to operate LCA concurrent to, or integrated with, these models is of growing importance.
Conclusions This paper outlines the historical development of such efforts in CLCA, discusses key methodological advancements, and characterizes previous literature on the topic. Based on this review, we provide an outlook for further research in CLCA.

Keywords Experience curves · CLCA · Partial equilibrium modeling · Computable general equilibrium modeling · Consequential life cycle assessment · Rebound effects

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1 Introduction

Over the past two decades, consequential life cycle assessment (CLCA) has emerged as a tool for capturing environmental impacts of product systems that go beyond physical relationships accounted for in attributional, or conventional, LCA (ALCA). Put simply, CLCA represents the convergence of LCA and economic modeling methods. For over a century, economists have sought to develop a method to quantify the impacts of economic relationships—such as substitution effects, economies of scale, and elasticities of supply and demand, among others (Marshall 1920). CLCA has connected many economic phenomena with life cycle environmental modeling of product and technological systems. While CLCA began with the use of simple economic models (see Ekvall 2000), increasingly sophisticated techniques have been adopted (see US EPA 2010). Since economic modeling can play a prominent role in national policy-making and strategic environmental planning, developing the capacity to operate LCA concurrent to, or integrated with, these economic models is of growing importance. This paper outlines the historical development of such efforts in CLCA, discusses key methodological advancements, and characterizes previous literature on the topic. Based on this review, we provide an outlook for further research in CLCA.

2 Historical and methodological development of LCA

LCA studies can be categorized into two general types: attributional and consequential. ALCA methodology accounts for immediate physical flows (i.e., resources, material, energy, and emissions) involved across the life cycle of a product. ALCA typically utilizes average data for each unit process within the life cycle. CLCA, on the other

hand, aims to describe how physical flows can change as a consequence of an increase or decrease in demand for the product system under study. Unlike ALCA, CLCA includes unit processes inside and outside of the product's immediate system boundaries. It utilizes economic data to measure physical flows of indirectly affected processes. Moreover, allocation is avoided in CLCA by expanding the system boundary (Weidema 2003).

The origins of CLCA first appeared as a discussion in Weidema (1993), which broadly outlined the need to consider market information in life cycle inventory (LCI) data. The author argued that when the purpose of performing an LCA is comparative, the actual environmental impacts are most realistically modeled by using environmental data on the affected technology.[1] According to Weidema (1993), in contrast to the accounting type, or “retrospective” LCA, comparative LCA[2] aims to study possible future changes between alternative product systems. Affected technology was described as the technology most likely to be affected by such future changes.[3] For example, while most Norwegian electricity is produced via hydropower plants, a small (or marginal) increase in electricity demand will likely result in an increase in fossil-based electricity production. This is due to capacity constraints on hydropower production and the relatively unconstrained and cheaper cost per kilowatt-hour of fossil-based electricity production.

In a study of municipal wastewater systems, Tillman et al. (1998) performed a comparative LCA study utilizing system boundary expansion[4]—an important aspect of CLCA. Tillman et al.’s (1998) method arose from the need to evaluate the environmental consequences of changing wastewater treatment systems in two Swedish villages among several systems under consideration. Employing the technique of system boundary expansion, they only modeled flows that would be affected by a change in wastewater treatment systems. For example, wastewater inflow constituents (i.e., food, dirt, detergents, etc.) were expected to be the same among all systems; and as a result were not modeled. Electricity produced from wastewater inflow constituents (via biogas), on the other hand, was included as it did not exist in the current system. By expanding the system boundary credits were then added to the wastewater system in response to the reduced need for electricity production of an equal utility. In doing this, however, Tillman et al. (1998) left a key question unanswered: How does one systematically identify which technologies or processes will be affected?

In response to this issue, Weidema et al. (1999) presented a step-wise approach for identifying affected technologies.[5] More specifically, in this procedure five questions drive the identification of affected technologies:

1. What time horizon does the study apply to?
2. Does the change only affect specific processes or a market?
3. What is the trend in the volume of the affected market?
4. Is there potential to provide an increase or reduction in production capacity?
5. Is the technology the most/least preferred?

The first question differentiates short-term and long-term time horizons, in which changes take place within existing production capacity or require additional capital investment (i.e., installing new machinery, etc.), respectively. Assuming a long-term time horizon, the second question identifies whether an affected technology exists as a foreground or background process. A foreground process should be modeled using site-specific data and is the affected technology. A background process, on the other hand, exists at the market level and requires further examination via step three. The third step differentiates between increasing and decreasing market trends. If market volume is generally decreasing, the affected technology will likely be an older, non-competitive (least preferred) technology. If market volume is generally increasing, the affected technology will likely be a more modern and competitive (most preferred technology) technology. The fourth question helps to determine if the technology under examination could provide the required increase or reduction in production capacity. This step aims to eliminate constrained technologies which cannot easily change capacity in response to a change in demand (hydropower in the example above). Finally, if the technology is unconstrained, it is necessary to select that which is preferred among those which remain. The most preferred technology will either be that which is most likely to be installed or phased out depending on market volume trends.

Weidema et al. (1999) and Weidema (2003) provide many examples of how the step-wise procedure can be applied across various markets, including agricultural, minerals/metals, forest-based, and plastics. The application of this procedure generally uses statistical databases (e.g.,

[1] Affected technology was originally referred to as marginal technology in Weidema’s earlier papers (e.g., Weidema et al. 1999)

[2] Comparative LCA would later be referred to as CLCA.

[3] Another definition forwarded by Weidema et al. (1999) for affected technology is the technology that changes its capacity/production in response to changes in demand.

[4] System boundary expansion was originally put forth by Tillman et al. (1991) and Vigon et al. (1993).

[5] At the time of publication, Weidema et al. (1999) referred to affected technologies as marginal technologies, but has more recently recommended that the term affected technologies be used to avoid confusion.

EuroStat[6] or FAOStat[7]) to determine market trends (step 3 above). Constraints on technology are specific to the market under examination and can be physical (e.g., land area in the case of agricultural production), technological (e.g., fermentation yields for ethanol production), economical (e.g., high cost to install additional capacity for nuclear power), or political (e.g., national emission caps on air pollutants). As a result, constraints can be determined from many possible data sources. With respect to identifying the affected technology among unconstrained ones, primary data (e.g., collected directly from producers/manufacturers) or secondary data sources are used to determine production costs. In the case of decreasing market trends, the highest costing technology per unit output will likely be affected via elimination. For an increasing market trend, the lowest costing technology per unit output will likely be affected via expansion.

In 2000, Bouman et al. began to investigate the similarities and differences between LCA and an economic technique called partial equilibrium (PE) modeling. PE models are typically used to analyze the possible effects of a policy on a market or set of markets (Francois and Hall 1997). Such models determine an equilibrium position among one or more markets by maximizing net social payoff.[8] PE modeling permits the investigation of substitutable and complementary goods as they relate to a change in price. They can be relatively small and simplified, or large models which incorporate hundreds of goods across multiple sectors. For instance, Bouman et al. (2000) construct a simple PE model which examines the effectiveness of several tax instruments on reducing the amount of mined, landfilled, and emitted lead from batteries. The Food and Agricultural Sector Optimization Model (FASOM), on the other hand, is a large PE model that includes hundreds of agricultural, forestry, and biofuel commodities, across 11 global market regions (Adams et al. 2005). These larger types of PE models can be categorized as Multi-Market, Multi-Region Partial Equilibrium Models (Roningen 1997), or MMMR-PE models.

Borrowing the microeconomic concept of price elasticity of supply and demand, Ekvall (2000) developed a quantitative technique for estimating indirect impacts in LCA using a simple two good PE model. The term indirect impact was introduced by Ekvall (2000) to denote environmental consequences that are outside of the physical supply chain, which instead result from market forces (e.g., product substitution). Ekvall (2000) used the context of open-loop recycling to demonstrate how price elasticity of supply and demand can inform consequential LCA studies. Given an increase in demand for old corrugated cardboard (OCC) to recycle, he wanted to know how much of this additional OCC supply will replace virgin pulp material and how much will replace OCC from other locations. Price elasticity of demand quantifies the percent change in demand for each percent change in price. For example, one statistical estimate suggests that if the price of OCC decreases by 1% then the quantity supplied decreases by 0.2% (Palmer et al. 1997). Similarly, they estimate that if the price of OCC decreases by 1%, the quantity demanded increases by 0.12%. The respective price elasticities of supply and demand are 0.2 and −0.12.[9] Thus, given a change in the amount of OCC collected for recycling, and knowing the price elasticities of supply and demand for OCC, Ekvall (2000) estimated the percentage of OCC which will likely replace virgin pulp and/or OCC from other locations. Environmentally, indirect impacts can occur by reducing the amount of virgin material produced and by increasing the amount of OCC from other locations to be landfilled.

While Bouman et al. (2000) suggested that PE and LCA models might best be used simultaneously and separately, Ekvall (2002) argued for the integration of PE models at first by softlinking and eventually through hardlinking.[10] Ekvall (2002) asserted that linking PE models could provide a technique for better modeling the consequences of change, especially indirect impacts, in LCA. Ekvall and Andrae (2006) developed a simple, softlinked PE and LCA model to explore the impacts of a ban of lead solder in the electronics industry. Since this study, other studies have applied a similar technique in the context of agricultural, energy, and real estate sectors. These studies are discussed in the following section of this paper.

Larger, existing MMMR-PE models have also been used to estimate life cycle impacts from indirect land-use change (ILUC) resulting from increased demand for biofuels. ILUC impacts can result, for instance, when additional biofuel demand increases the amount of land dedicated to corn production (Searchinger et al. 2008). This increased demand can result in the plowing of forest or grasslands releasing longer-term carbon stored in the soil. Alternatively, farmers can divert existing crops or croplands to biofuel production. As a result, prices for the crop rise, leading to land conversion internationally to meet additional demand. Searchinger et al. (2008) utilized a Food and

[6] http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/search_database

[7] http://faostat.fao.org/default.aspx

[8] Net social payoff is defined as the sum of consumer and producer surplus (Francois and Hall 1997).

[9] Based on the laws of supply and demand, price elasticities of supply and demand are positive and negative, respectively.

[10] Ekvall (2002) states that softlinking manually feeds the results of one model into the other, while hardlinking combines two types of models into a single model

Agricultural Policy Research Institute (FAPRI) PE model[11] to estimate ILUC impacts with respect to greenhouse gases (GHGs). More recently, the US Environmental Protection Agency (EPA) has expanded this initiative combining the FAPRI and FASOM models in support of national biofuel policy (US EPA 2010). Importantly, such models provide a spatial resolution of production, which can have unique environmental impacts (depending on local political and environmental conditions) for the same product output.

Computable general equilibrium (CGE) models provide another method for estimating indirect impacts in LCA. Similar to PE modeling, CGE models are typically used to model policy effects via the assumption of maximizing agents. Unlike PE models, however, CGE includes all sectors within the economic system. While CGE models are more comprehensive than PE models, they typically lack the amount sectoral level detail (Ekvall 2002). Kløverpris et al. (2008) developed a framework to softlink a CGE model called the Global Trade Analysis Project (GTAP) with LCA to estimate ILUC impacts with respect to agricultural markets. GTAP outputs change among 57 economic sectors across 87 regions as a result of a "shock" in demand, supply, policy, etc. Kløverpris (2009) utilized GTAP to estimate land area of affected ecosystem biomes based on the location of land-use change. This novel LCI metric would then feed into a life cycle impact assessment (LCIA) method to determine impacts associated land conversion by biome. The US EPA also used GTAP to estimate ILUC impacts (i.e., GHGs and regulated pollutants) associated with national biofuel policy (US EPA 2010).

Moreover, CLCA models can reveal valuable information regarding "rebound effects" (Ekvall 2002). There are two types of rebound effects: direct and indirect (Hofstetter and Norris 2003). Direct rebound effects occur when greater efficiency lowers the price for a service which increases the use of this cheaper service. As an example, a change in energy efficiency for an air conditioning unit could lower the price of cooling, leading to increased usage. Indirect rebound effects occur when efficiency lowers the price of production for a commodity, thus freeing up more consumer income to be spent on other goods—assuming that prices of other commodities and income are constant. An example of an indirect rebound effect is the advancement of computer technology. As the price of personal computers falls due to gains in production efficiency, available consumer income (due to cheaper computers) can be spent on other goods (see Thiesen et al. 2008 for another example). Efficiencies in time use can also result in rebound effects. For example, the result of shifting the speed limit on a popular highway from 100 to 130 kph could result in people travelling longer distances—thus, creating more emissions and burning more fuel. Both indirect and direct rebound effects can be highly relevant when calculating environmental impacts due to a change in production, also known as environmental rebound effects (Spielmann et al. 2008). In the literature, rebound effects are likely grouped under CLCA because they occur as a consequence of a decision and are determined using market information.

Other economic tools have been integrated with CLCA techniques to create hybrid methodologies. Sanden and Karlstrom (2007) incorporate experience curves and learning effects into CLCA. An experience curve empirically models the relationship between cumulative production and unit cost (Argote and Epple 1990). A power function is typically used to describe this inverse relationship. In other words, as cumulative production experience increases (typically measured in labor hours) the production cost per good decreases—levelling out at some constant once the technology becomes well established. Sanden and Karlstrom (2007) propose that if a certain investment is needed to realize learning and economies of scale until the point where the technology is competitive, then the technology could be credited a share of emission reduction in proportion to its share of the total required learning investment. They provide the example of hydrogen fuel cell bus technology. Compared to a baseline scenario in which fossil energy sources dominate the market over the next century, high investment today in hydrogen technology development would accumulate experience and ultimately drive down the cost of production. Sanden et al. (2007) argue that the future environmental reductions from the baseline scenario could be credited to hydrogen technology today proportionate to the amount invested. They suggest that this method more accurately represents the real environmental impacts resulting from adoption of hydrogen technology. Pehnt et al. (2008), as another example, softlink the output from a stochastic model of the European electricity market with LCA to more accurately determine affected technologies from adopting offshore wind technology.

Seminal papers driving the historical and methodological development of CLCA are discussed above. The following section characterizes prior CLCA studies in light of this background information.

3 Characterization of past literature

Overall, 25 articles were selected for review in this analysis of past literature. Only applications of CLCA are included in Table 1. Strictly theoretical papers are mentioned above

[11] See US EPA (2010) for more information on the FAPRI model used to assess the ILUC impacts associated with US biofuel policy

Table 1 Applications of CLCA

Reference	Topic	CvA	SWA	PEM	MMMR-PEM	CGE	ILUC	RE	Notes
Hofstetter and Norris (2003)	Occupational Health	Y	N	N	N	N	N	Y	Framework for CLCA w/r/t occupational health impacts; argues for inclusion of changes in unemployment and substitution effects in labor market
Weidema (2003)	Many topics	N	Y	N	N	N	N	N	Extension of Weidema et al. (1999)
Ekvall and Andrae (2006)	Electronics	Y	Y	Y	N	N	N	N	Extension of Ekvall (2000) to electronics industry
Thrane (2006)	Fishing	N	Y	N	N	N	N	N	Application of Weidema et al. (1999)
Lesage et al. (2007a)	Brownfields	N	N	Y	N	N	N	N	Extension of Ekvall (2000) to brownfields
Lesage et al. (2007b)	Brownfields	Y	N	Y	N	N	N	N	Extension of Ekvall (2000) to brownfields
Eriksson et al. (2007)	Heating	N	N	N	N	N	N	N	Optimization model of EU energy market used to determine affected technology
Sanden and Karlstrom (2007)	Renewable fuels	N	Y	N	N	N	N	N	Experience curves introduced into CLCA
Schmidt et al. (2007)	Paper	N	Y	N	N	N	N	N	Application of Weidema et al. (1999)
Spielmann et al. (2008)	Mass transit	N	N	N	N	N	N	Y	Rebound effects associated with changes in mobility patterns due to time savings
Thiesen et al. (2008)	Consumer goods	N	N	N	N	N	N	Y	Rebound effect of price differences between products on consumption
Kløverpris et al. (2008)	Agriculture	N	N	N	N	Y	Y	N	Utilizes CGE model (GTAP) to estimate ILUC from agricultural expansion
Dalgaard et al. (2008)	Agriculture	N	N	Y	Y	N	N	N	Utilizes economic model ESMERALDA to identify affected technology
Schmidt and Weidema (2008)	Agriculture	N	Y	N	N	N	Y	N	Augments Weidema et al. (1999) and Ekvall (2000); agricultural statistics and outlooks to determine affected technologies
Schmidt (2008a)	Agriculture	N	Y	N	N	N	Y	N	Augments Weidema et al. (1999) and Ekvall (2000); agricultural statistics and outlooks to determine affected technologies
Schmidt (2008b)	Agriculture	N	Y	Y	N	N	Y	N	LCIA of land-use change with respect to biodiversity
Thomassen et al. (2008)	Agriculture	Y	Y	Y	N	N	Y	N	Application of Schmidt and Weidema (2008)
Frees (2008)	Metals	N	N	Y	N	N	N	N	Application of Ekvall (2000)
Pehnt et al. (2008)	Electricity	N	N	N	N	N	N	N	Coupling LCA and stochastic European electricity market model
Searchinger et al. (2008)	Biofuel	N	N	Y	Y	N	Y	N	Use of FAPRI PE model to estimate ILUC impacts with respect to US biofuels policy
Vieira and Horvath (2008)	Buildings	Y	Y	Y	N	N	N	N	Application of Weidema et al. (1999) and Ekvall (2000) to building end-of-life stage
Kløverpris (2009)	Agriculture	N	N	N	N	Y	Y	N	Kløverpris et al. (2008) + biomes characterization
Reinhard and Zah (2009)	Biofuel	Y	Y	Y	N	N	Y	N	Application of Schmidt and Weidema (2008)
Silalertruksa et al. (2009)	Biofuel	N	Y	Y	N	N	Y	N	Application of Schmidt and Weidema (2008)

Table 1 (continued)

Reference	Topic	CvA	SWA	PEM	MMMR-PEM	CGE	ILUC	RE	Notes
US EPA (US 2010)	Biofuel	N	N	Y	Y	Y	Y	N	Use of large FAPRI AND FASOM PE models, and GTAP CGE model to determine ILUC impacts with respect to US biofuels policy
Kløverpris et al. (2010)	Agriculture	N	N	N	N	Y	Y	N	Application of Kløverpris et al. (2008)

CvA comparison of consequential and attributional LCA, *SWA* use of step-wise approach to identifying affected technology (from Weidema et al. 1999), *PEM* partial equilibrium modeling, *MMMR-PEM* Multi-Market, Multi-Regional Partial Equilibrium Modeling, *CGE* computable general equilibrium modeling, *ILUC* indirect land-use change examined, *RE* rebound effects examined

and not included in the table. Several seminal papers (e.g., Ekvall (2000) and Weidema et al. (1999)) are not included in this table, as they are discussed above. Also, we do not include Ekvall and Weidema (2004) which provides a comprehensive review of CLCA until 2004, and importantly combines the methods of Weidema et al. (1999) and Ekvall (2000) in a single article. We provide a breakdown according to the general topic to which CLCA was applied. Additionally, we characterize these studies according to some of the key aspects of CLCA discussed previously, such as Weidema et al.'s (1999) step-wise approach to identifying affected technologies, PE modeling, rebound effects, and so on. Moreover, notes are provided which give further detail about any unique or identifying aspects of the study.

3.1 Attributional versus consequential LCA

In this review, we identify six articles which performed both ALCA and CLCA for the purpose of comparison. The topics covered include occupational health, electronics, brownfields, agriculture, buildings, and biofuels. The debate on how and when to perform ALCA versus CLCA is not yet resolved (Zamagni et al. 2008). The identification of affected technologies, collection of marginal data (i.e., which technologies will be affected and how much), and associated uncertainties are at the center of this controversy. Tillman (2000) argues that it will be hard to establish consensus on how to identify affected technologies and collect marginal data. Moreover, Tillman (2000) asserts that ALCA provides a simpler framework with smaller system boundaries, which implies less data collection. Contrarily, Weidema (2003) argues that due to the exclusion of unchanged unit processes, CLCA will typically require less data collection despite system boundary expansion. From a theoretical perspective, Weidema et al. (1999) argues that ALCA has little to no relevance—even to hot-spot identification, environmental product declarations, or as generic consumer information. He states that

> "outside of a consequential context, any separation of product systems will be inherently normative i.e.: "Providing we use method X for dividing car driving from the rest of the technosphere, what is its environmental contribution?" implying that the question carries the premises for its own answer" (Weidema 2003).

The main concern of Weidema (2003) is that ALCA determines system boundaries normatively, instead of basing system delimitation decisions on causality or consequences reflective of real-world behavior.

Of the articles reviewed, marginal data collection generally appeared to be challenging, mostly due to

unavailability of such information. For example, Ekvall and Andrae (2006) could not find information on the marginal use of electricity for the EU. In addition, representative data was used in place of marginal data for several other subsystems. Vieira and Horvath (2008) encountered a similar difficulty in identifying marginal data with respect to building industry. Schmidt (2008), on the other hand, more successfully develops estimates for identifying affected agricultural technologies using the step-wise approach introduced by Weidema et al. (1999). Thomassen et al. (2008) and Reinhard and Zah (2009) successfully apply the technique developed by Schmidt (2008). In addition, Thomassen et al. (2008) note that an equivalent amount of data collection was required when performing CLCA and ALCA.

While data collection is currently an obstacle for CLCA, the method can reveal unique environmental insights beyond ALCA. Ekvall and Andrae (2006) found that ALCA revealed that the shift from lead-containing to lead-free solder means that lead is virtually eliminated from the solder life cycle. CLCA, on the other hand, showed to what extent the shift reduces overall use of lead, how lead use will increase in other life cycles and, in the products in which lead use will increase when the metal is eliminated from solder paste. Lesage et al. (2007b) likewise found that CLCA uniquely captures the aspect of site fate in the context of brownfield redevelopment, whereas ALCA does not. Thomassen et al. (2008) found differences between ALCA and CLCA in total quantitative outcomes, hotspots, and degrees of understanding among stakeholders. On the other hand, with respect to building end-of-life Vieira and Horvath (2008) found little difference between the ALCA and CLCA results.

3.2 Integrating larger, more complex economic models with CLCA

The first efforts to account for indirect environmental impacts in LCA appealed to simple partial equilibrium models (i.e., Ekvall 2000) and heuristic methods for identifying affected technologies (i.e., Weidema et al. 1999). Over the past 10 years, however, researchers have expanded from these initial developments to more complex and comprehensive economic models. More specifically, the move toward MMMR-PE models and CGE models demonstrates this trend. One early example of a study that used MMMR-PE modeling is Dalgaard et al. (2008). They utilize a Dutch agricultural model to identify marginal rapeseed and spring barley producers among the 31 farm types, so that marginal Danish data and not average data were used. Searchinger et al. (2008) utilized FAPRI to project the affected technologies associated with an increase in demand for corn-based ethanol. More recent efforts, by the US EPA expanded on Searchinger et al. (2008) to include the FASOM model as well. These models provide a high-level of detail specific to agriculturally related markets. Due to this limited focus, however, it is not immediately clear whether such MMMR-PE models are available for other sectors (e.g., electronics, minerals, metals, etc.). Furthermore, no effort to identify and review available MMMR-PE models in terms of relevance to LCA has been performed. This is clearly an important step in understanding the sectors for which such models exist and at what level of detail.

Also demonstrating the trend toward integrating larger, more complex economic models and CLCA, is the use of GTAP by Kløverpris et al. (2008) and US EPA (2010) to determine affected technologies across the global economy. While CGE models provide more comprehensive output with respect to number of sectors and regions included, product sector resolution is very low. As a result, it is not clear what the actual affected product is beyond generic sector categories. This could be a challenge with respect to matching LCI data to general market sectors. For example, LCI data typically represents a specific product system or an average product system. On the other hand, CGE models (such as GTAP) only have 57 economic sectors. Thus, it could be necessary to create aggregate LCI datasets weighted by market-share to represent a sector's unit output.

The spatial resolution provided by many MMMR-PE and CGE models opens new opportunities for research on indirect impacts associated with specific geographic regions. As a hypothetical example, an increased demand for wood-based biofuel could shift some paper production to Indonesia. Regulatory, production, and geographical factors in Indonesia would likely be different from the USA. Fewer emission regulations may exist. Biomass production will likely involve different species and cultivation techniques. Moreover, holding LCI values constant per unit biofuel, a unique set of LCIA values will exist depending on local geographic features (Earles and Halog 2010a, 2010b). The capacity of MMMR-PE and CGE models to geographically identify changes in production aligns with concurrent efforts to regionalize LCI and LCIA datasets (e.g., Steinberger et al. 2009; Wegener Sleeswijk and Heijungs 2010; Gallego et al. 2010).

Rebound effects and experience curves represent complex economic phenomena that can lead to indirect environmental impacts. We only identified a few studies that examined rebound effects in the context of LCA. Moreover, only one study has investigated the integration of experience curves and LCA. Both of these topics represent opportunities for further research. One field that was not present in the literature reviewed is system dynamics. Future research might work to advance CLCA

by linking to the well-established field of system dynamics, particularly with relevance to causality or consequences reflective of real-world behavior (Halog and Manik 2011).

4 Conclusions

CLCA began as an effort to incorporate market information into LCA to avoid the problem of normatively cutting-off a product's system boundary. Since this initial goal, CLCA has been the object of much research and debate. Consensus on when to use CLCA and standardizing the CLCA procedure are still under development. While initial efforts relied on simple PE modeling and a heuristic approach to determining affected technologies, more recent techniques incorporate sophisticated economic models for this purpose. In line with Zamagni et al. (2008), we suggest that further research should be focused at the intersection of PE and CGE modeling with CLCA. We go further to distinguish between simple PE modeling and MMMR-PE modeling, suggesting that the latter better represents the state-of-the-art in economic methods. The relevance of incorporating other economic mechanisms into CLCA should also be explored, as is the case with rebound effects and experience curves.

References

Adams D, Alig R, McCarl B et al. (2005) FASOMGHG Conceptual Structure and Specification: Documentation. Retrieved September 28, 2010 from: http://agecon2.tamu.edu/people/faculty/mccarl-bruce/papers/1212FASOMGHG_doc.pdf

Argote L, Epple D (1990) Learning curves in manufacturing. Science 247:920–924

Bouman M, Heijungs R, van der Voet E, van den Bergh JCJM, Huppes G (2000) Material flows and economic models: an analytical comparison of SFA, LCA and partial equilibrium models. Ecol Econ 32:195–216

Dalgaard R, Schmidt J, Halberg N, Christensen P, Thrane M, Pengue WA (2008) LCA of soybean meal. Int J Life Cycle Assess 13 (3):240–254

Earles JM, Halog A (2010a) Partial Equilibrium Modeling and LCA in the Forest Biorefinery Context. Proceedings from Cycle 2010—4th Canadian Forum on the Life Cycle Management of Products and Services. Presented on May 4th, 2010

Earles JM, Halog A (2010b) Integrating Partial Equilibrium Modeling and LCA in the Forest Biorefinery Context. Proceedings from Life Cycle Assessment X Conference. Presented on November 3 rd, 2010. <http://www.lcacenter.org/LCAX/presentations-final/184.pdf>

Ekvall T (2000) A market-based approach to allocation at open-loop recycling. Resour Conserv Recycl 29(1–2):91–109

Ekvall T (2002) Cleaner production tools: LCA and beyond. J Clean Prod 10(5):403–406

Ekvall T, Andrae A (2006) Attributional and consequential environmental assessment of the shift to lead-free solders. Int J Life Cycle Assess 11(5):344–353

Ekvall T, Weidema B (2004) System boundaries and input data in consequential life cycle inventory analysis. Int J Life Cycle Assess 3:161–171

Eriksson O, Finnveden G, Ekvall T, Bjorklund A (2007) Life cycle assessment of fuels for district heating: a comparison of waste incineration, biomass- and natural gas combustion. Energy Policy 35(2):1346–1362

Francois JF, Hall HK (1997) Partial equilibrium modeling. In: Francois J, Reinert K (eds) Applied methods for trade policy analysis, 1st edn. Cambridge University Press, Cambridge, pp 122–155

Frees N (2008) Crediting aluminium recycling in LCA by demand or by disposal. Int J Life Cycle Assess 13(3):212–218

Gallego A, Rodriguez L, Hospido A, Moreira MT, Feijoo G (2010) Development of regional characterization factors for aquatic eutrophication. Int J Life Cycle Assess 15:32–43

Halog A, Manik Y (2011) Advancing integrated system modeling framework for life cycle sustainability assessment. Sustainability 3(2):469–499

Hofstetter P, Norris GA (2003) Why and how should we assess occupational health impacts in integrated product policy? Environ Sci Technol 37(10):2025–2035

Kløverpris J (2009) Identification of biomes affected by marginal expansion of agricultural land use induced by increased crop consumption. J Clean Prod 17(4):463–470

Kløverpris J, Wenzel H, Nielsen P (2008) Life cycle inventory modeling of land use induced by crop consumption part 1: conceptual analysis and methodological proposal. In J Life Cycle Assess 13(1):12–21

Kløverpris JH, Baltzer K, Nielsen PH (2010) Life cycle inventory modelling of land use induced by crop consumption part 2: example of wheat consumption in Brazil, China, Denmark and the USA. Int J Life Cycle Assess 15:90–103

Lesage P, Ekvall T, Deschenes L, Samson RJ (2007) Environmental assessment of brownfield rehabilitation using two different life cycle inventory models: part 1. Int J Life Cycle Assess 12 (7):497–513

Lesage P, Ekvall T, Deschenes L, Samson, RJ (2007b) Environmental assessment of brownfield rehabilitation using two different life cycle inventory models: part 2. Int J Life Cycle Assess 12(7):497–513

Marshall A (1920) Principles of Economics. Library of Economics and Liberty. Retrieved September 28, 2010 from: http://www.econlib.org/library/Marshall/marP33.html

Palmer K, Sigman H, Walls M (1997) The cost of reducing municipal solid waste. J Environ Econ Manage 33:128–150

Pehnt M, Oeser M, Swider DJ (2008) Consequential environmental system analysis of expected offshore wind electricity production in Germany. Energy 33(5):747–759

Reinhard J, Zah R (2009) Global environmental consequences of increased biodiesel consumption in Switzerland: consequential life cycle assessment. J Clean Prod 17(S1):46–56

Roningen VO (1997) Multi-market, multi-region partial equilibrium modeling. In: Francois J, Reinert K (eds) Applied methods for trade policy analysis, 1st edn. Cambridge University Press, Cambridge, pp 231–257

Sanden BA, Karlstrom M (2007) Positive and negative feedback in consequential life-cycle assessment. J Clean Prod 15(15):1469–1481

Schmidt JH (2008) System delimitation in agricultural consequential LCA. Int J Life Cycle Assess 13(4):350–364

Schmidt JH, Weidema B (2008) Shift in the marginal supply of vegetable oil. Int J Life Cycle Assess 13(3):235–239

Schmidt JH, Holm P, Merrild A, Christensen P (2007) Life cycle assessment of the waste hierarchy—a Danish case study on waste paper. Waste Manage 27(11):1519–1530

Searchinger T, Heimlich R, Houghton R, Dong F, Elobeid A, Fabiosa J, Tokgoz S, Hayes D, Yu T (2008) Use of U.S. croplands for

biofuels increases greenhouse gases through emissions from land-use change. Science 319(5867):1238–1240

Silalertruksa T, Gheewala SH, Sagisaka M (2009) Impacts of Thai bio-ethanol policy target on land use and greenhouse gas emissions. Appl Energy 86:S170–S177

Spielmann M, de Haan P, Scholz RW (2008) Environmental rebound effects of high-speed transport technologies: a case study of climate change rebound effects of a future underground maglev train system. J Clean Prod 16(13):1388–1398

Steinberger JK, Friot D, Jolliet O, Erkman S (2009) A spatially explicit life cycle inventory of the global textile chain. Int J Life Cycle Assess 14:443–455

Thiesen J, Christensen T, Kristensen T, Andersen R, Brunoe B, Gregersen T, Thrane M, Weidema B (2008) Rebound effects of price differences. Int J Life Cycle Assess 13(2):104–114

Thomassen M, Dalgaard R, Heijungs R, de Boer I (2008) Attributional and consequential LCA of milk production. Int J Life Cycle Assess 13(4):339–349

Thrane M (2006) LCA of Danish fish products: new methods and insights. Int J Life Cycle Assess 11(1):66–74

Tillman A-M, Baumann H, Eriksson E, Rydberg T (1991) Life cycle analysis of packaging materials. Calculation of environmental load. Chalmers Industriteknik, Göteborg

Tillman A-M, Svingby H, Lundstrom H (1998) Life cycle assessment of municipal waste water systems. Int J Life Cycle Assess 3 (3):145–157

Tillman A-M (2000) Significance of decision making for LCA methodology. Environ Impact Assess Rev 20:113–123

US EPA (2010) Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis. EPA-420-R-10-006. February, 2010

Vieira PS, Horvath A (2008) Assessing the end-of-life impacts of buildings. Environ Sci Technol 42(13):4663–4669

Vigon BW, Tolle DA, Cornaby BW et al. (1993) Life cycle assessment: Inventory guidelines and principles. Washington D.C. & Cincinnati: United States Environmental Protection Agency, Office of Research and Development. (EPA/600/R-92/245)

Wegener Sleeswijk A, Heijungs R (2010) GLOBOX: a spatially differentiated global fate, intake and effect model for toxicity assessment in LCA. Sci Total Environ 408(14):2817–2832

Weidema BP (1993) Market aspects in product life cycle inventory methodology. J Clean Prod 1(3–4):161–166

Weidema BP (2003) Market information in life cycle assessment. Copenhagen: Danish Environmental Protection Agency. (Environmental Project no. 863): http://www2.mst.dk/Udgiv/publications/2003/87-7972-991-6/pdf/87-7972-992-4.pdf

Weidema BP, Frees N, Nielsen A (1999) Marginal production technologies for life cycle inventories. Int J Life Cycle Assess 4 (1):48–56

Zamagni A, Buttol P, Porta PL, Buonamici R, Masoni P, Guinée J, Heijungs R, Ekvall T, Bersani R, Biekowska A, Pretato U (2008) Critical review of the current research needs and limitations related to ISO-LCA practice. Deliverable D7 of Work Package 5 of the CALCAS project: http://fr1.estis.net/sites/calcas/default.asp?site=calcas&page_id=E2669B0F-9DB7-4D1E-95B0-407BC7949030